Extending integrated assessment models damage functions to include adaptation and dynamic sensitivity

Estrada, Francisco; Tol, Richard S.J.; Botzen, W. J.Wouter

published in
Environmental Modelling and Software
2019

DOI (link to publisher)
10.1016/j.envsoft.2019.104504

Environmental Modelling and Software 121 (2019) 104504

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Extending integrated assessment models' damage functions to include adaptation and dynamic sensitivity

Francisco Estrada[a,b,*], Richard S.J. Tol[c,b,d,e,f,g], W.J. Wouter Botzen[b,h]

[a] Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Ciudad Universitaria, Circuito Exterior, 04510, DF, Mexico
[b] Institute for Environmental Studies, Vrije Universiteit, Amsterdam, the Netherlands
[c] Department of Economics, University of Sussex, Falmer, United Kingdom
[d] Department of Spatial Economics, Vrije Universiteit, Amsterdam, the Netherlands
[e] Tinbergen Institute, Amsterdam, the Netherlands
[f] CESifo, Munich, Germany
[g] Payne Institute for Earth Resources, Colorado School of Mines, Golden, CO, USA
[h] Utrecht University School of Economics (U.S.E.), Utrecht University, Utrecht, 3508 TC, the Netherlands

ARTICLE INFO

Keywords:
Integrated assessment model
Economic costs of climate change
Adaptation
System dynamics
Coping range

ABSTRACT

Through stylized damage functions, Integrated Assessment Models (IAMs) provide estimates of the economic costs that would occur for absolute changes in global temperature. In these damage functions, adaptation, sensitivity and their interactions are often combined in an intractable way. In this theoretical study we propose a new type of damage functions that allows mapping economic losses in terms of how extreme global temperature changes are in relation to a coping range representing the capacity of a system to deal with the climate conditions experienced at a particular period of time. In these new damage functions, which can be applied to the regional and global scales, adaptation to a changing climate is introduced by allowing the reference climate to be a function of time instead of a fixed quantity. Different formulations of damage functions discussed in the literature arise as special cases.

1. Introduction

Integrated Assessment (IA) and Integrated Assessment Models (IAMs) have been widely used to address complex environmental problems (e.g., Döll et al., 2013; Nordhaus, 2008, 2017; Akhtar et al., 2013; de Vos et al., 2013). IA/IAMs allow to integrate the knowledge from different disciplines and provide a consistent way for analyzing and exploring the consequences of environmental problems and the effects of different response actions (e.g., Füssel, 2010; Vedrenne et al., 2014; Hamilton et al., 2015; Kelly et al., 2013; Letcher et al., 2007). Significant efforts have been made to identify and overcome important shortcomings in IAMs (e.g., Jakeman et al., 2006; Schwanitz, 2013; Schneider, 1997; Tol, 2018), and to improve the understanding regarding both implicit and explicit assumptions as well as the sensitivity of parameter values (e.g., Botzen et al., 2018; Estrada et al., 2015; Butler et al., 2014; Nordhaus, 2008; see also the *Thematic Issue on Innovative Approaches to Global Change Modelling* in Volume 44 of *Environmental Modelling and Software*).

In this study, we focus on IAMs of economic impacts of climate change. The function that relates climate change to its impacts is crucial for any assessment of the seriousness of climate change (e.g., Diaz and Moore, 2017; Estrada et al., 2015; Tol and Fankhauser, 1998). IAMs often use stylized damage functions with implicit adaptation, and a sensitivity to climate change that is the same for all warming trajectories and path-independent. Most of these damage functions are inherently static and do not allow for interactions between impacts, sensitivity and adaptation. Using empirical estimates of persistence of general shocks to observed GDP, Estrada et al. (2015) showed that the projected economic costs of climate change could have been severely underestimated in past assessments. However, that study only included the dynamics of impacts without explicitly accounting for dynamics in adaptation and sensitivity of the system affected by climate change. The present work extends what is presented in Estrada et al. (2015) by proposing a theoretical specification of an adjusted climate change damage function that explicitly incorporates a tractable generalization of adaptation and sensitivity dynamics.

* Corresponding author. Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, México.
E-mail address: feporrua@atmosfera.unam.mx (F. Estrada).

https://doi.org/10.1016/j.envsoft.2019.104504
Received 15 October 2018; Received in revised form 19 August 2019; Accepted 20 August 2019
Available online 23 August 2019

Software and data availability

Microsoft Excel and Microsoft Excel Solver were used for producing the results in this paper (https://products.office.com/en/excel)
An Excel file to reproduce the figures in this paper is available at https://figshare.com/s/4ced4e083b9906a4cfb3. MATLAB was used for Figure A3 (https://in.mathworks.com/products/matlab.html)
The HadCRUT4 near surface temperature data set used in this paper is available at http://www.metoffice.gov.uk/hadobs/hadcrut4/data/4.2.0.0/download.html.

The objective of this paper is to study the dynamics of adaptation and the sensitivity of economic welfare to climate change. In particular, we aim to answer the following research questions: Which kind of damage function can suitably account for such dynamics? What are the implications for the estimated economic impacts of climate change? We derive the mathematical properties of this damage function and illustrate numerically that these dynamics matter for estimates of the impacts of climate change.

The most common damage function in IAMs is a polynomial function of global temperature (e.g., Warren et al., 2006):

$$D_t = \alpha_1 T_t + \alpha_2 T_t^{\alpha_3} \tag{1}$$

where D_t are the damages occurring at time t due to changes in average global or regional temperatures anomalies (T_t) with respect to a reference period (frequently the pre-industrial climate) and $\alpha_1 = \alpha_1^*$, $\alpha_2 = \alpha_2^*$ are fixed parameters fitted for a certain increase in global temperature (e.g., 2.5 °C or a doubling of the atmospheric concentration of CO2), and frequently $\alpha_3 = 2$. Damage functions are usually fitted for smooth and deterministic climate change (Estrada and Tol, 2015). This implies that T_t only represents the response to changes in radiative forcing and does not include natural variability.

In general, impacts can be conceptualized as a function of changes in climate (hazard), sensitivity, and adaptive capacity. In Equation (1) these three determinant factors and their interactions are combined in an intractable way (e.g., Tol and Fankhauser, 1998; Tol et al., 1998; Patt et al., 2010; Füssel, 2010). No impact dynamics are allowed and for any particular value of T_t, the sensitivity of the system affected by climate change is fixed and does not depend on past impacts (see Estrada et al., 2015). For instance the standard DICE model uses Equation (1), which implies that adaptation is accounted for implicitly by fitting the damage function to estimates of climate damages net of adaptation (Nordhaus, 2017). In the FUND model, adaptation in agriculture is modelled explicitly by a lagged rate component that fades with adaptation; adaptation to sea level rise impacts is based on a cost-benefit analysis; while for other impacts adaptation is implicit by fitting the damage function on net impacts (Diaz and Moore, 2017). A few existing studies are exceptions in that they explicitly model adaptation in IAMs of climate impacts on the economy. In AD-DICE, De Bruin et al. (2009a,b) explicitly model adaptation in DICE by separating adaptation to absolute climate change damages from climate impacts, which allows for examining tradeoffs between greenhouse gas mitigation and adaptation policies. In PAGE adaptation is modelled explicitly through exogenous fixed regional policies that reduce climate impacts for a cost (Hope, 2011). Dumas and Ha-Duong (2013) model transient adaptation cost of adaptation to a changing climate system in an IAM by integrating protection capital in a Cobb-Douglas production function. Bosello and De Cian (2014) adjust the damage functions in the WITCH model of economic climate impacts to account for adaptation costs and effectiveness in climate damage functions for different economic sectors and regions. Others have estimated the impacts of climate change with climate variability as input in the damage function. For instance, Lempert et al. (2000) add two components to the commonly used power law damage function based on global-mean surface temperature: namely impacts due to changes in climate variability to which can be adapted in a two-year time-scale, and impacts due to changes in climate variability to which adaptation occurs more slowly and takes a few decades.

We propose a new damage function based on a transformation that "standardizes" changes in climate by means of the system's coping range and adaptive capacity. A novelty of our approach is that both the system's sensitivity and adaptive capacity are dynamic and explicit. Current IAMs assume that impacts depend on absolute changes in climate variables. We instead model economic impacts as a function of the difference between actual and expected climate conditions, relative to society's ability to adapt. Models of complex systems, such as IAMs, are inherently heuristic and aim to help thinking and learning about selected traits of the systems under study and their interactions, as well as for performing what-if analyses (Oreskes et al., 1994). When modelling these systems, large simplifications and idealizations are made, information is incomplete or fragmented, and deep uncertainty is characteristic[1] (Gay and Estrada, 2010; Spiegelhalter and Riesch, 2011; Baumberger et al., 2017). Full fitting of these models, as well as their evaluation or verification, is hardly possible (Oreskes et al., 1994; Oreskes, 1998). Here, the proposed damage function is fitted to reproduce the results of the AD-DICE damage function (De Bruin et al., 2009a) for the static case. Sensitivity analyses are presented and possible alternative representations are discussed for the new parameters in the new damage function. The material presented in this paper contributes to the literature by highlighting the importance of dynamics of adaptation and sensitivity when estimating the economic impacts of climate change, which can serve as a basis for further research on these topics.

The paper is structured as follows. Section 2 presents a generalization of the damage functions. In Section 3 some of the damage functions commonly used in the literature are adjusted for accommodating the modifications proposed in Section 2 and for discussing the underlying implications of current damage functions in IAMs. The conclusions and future extensions of this paper are presented in Section 4.

2. A generalization of damage functions

Consider the following generalization of the damage function in Equation (1):

$$D_t^{ad} = \alpha_1 S_t + \alpha_2 S_t^{\alpha_3} \tag{2}$$

where

$$S_t = \frac{T_t - a_t}{\sigma_t} \tag{3}$$

σ_t represents the coping range of the system which is a measure of its sensitivity to changes in T_t. a_t is the temperature change the system is adapted to at time t. Therefore, D_t^{ad} are the economic damages of climate change (% of GDP) taking into account the current values of adaptation and coping range. $t = 1, \ldots, T$ is discrete and the time step is annual. In the case of stationary climate there are no impacts, because the climate is as expected (i.e., the observed climate is the same as the reference climate, therefore the change in T_t is equal to zero). Both σ_t and a_t are expressed in °C and S_t is thus unitless (see Table A1 for a description of all parameters and variables). Note that the "standardization" of T_t in Equation (3) is not conducted to reflect the statistical

[1] Deep uncertainty refers to the situation in which analysts don't know or cannot agree upon: 1) the adequate models to describe the system's interactions; 2) the probability distributions, key variables or parameters in these models; and 3) the value of the alternative outcomes (Walker et al., 2013).

properties of T_t. In this re-expression, the impacts become a function of how extreme the climate conditions are for a given system with particular coping and adaptation capacities, instead of absolute temperature changes.[2]

Through adaptation, the system can migrate to a new set of normal climate conditions. In this way, the climate of reference in Equations (2) and (3) above is time-dependent, and the damage function thus changes over time too.

From (2) and (3) we have

$$D_t^{ad} = \frac{\alpha_1}{\sigma_t}(T_t - a_t) + \frac{\alpha_2}{\sigma_t^{\alpha_3}}(T_t - a_t)^{\alpha_3} = \beta_{1,t}(T_t^*) + \beta_{2,t}(T_t^*)^{\alpha_3} \tag{4}$$

where $\beta_{1,t} = \frac{\alpha_1}{\sigma_t}$, $\beta_{2,t} = \frac{\alpha_2}{\sigma_t^{\alpha_3}}$ and $T_t^* = T_t - a_t$. Making σ_t a function of time is equivalent to having a damage function with time-varying parameters, which reflects changes in the sensitivity of the system to net changes in temperature (T_t^*).

If a regional dimension is considered, Equation (4) can be generalized to

$$D_{r,t}^{ad} = \frac{\alpha_1}{\sigma_{r,t}}(T_{r,t} - a_{r,t}) + \frac{\alpha_2}{\sigma_{r,t}^{\alpha_3}}(T_{r,t} - a_{r,t})^{\alpha_3} = \beta_{1,r,t}(T_{r,t}^*) + \beta_{2,r,t}(T_{r,t}^*)^{\alpha_3} \tag{5}$$

where the coefficients of the r regions are explicitly scaled by their sensitivity, giving an alternative approach for producing regional models.[3]

2.1. Specification of adaptation in the proposed damage function

Adaptation can be represented as the sum of planned and autonomous adaptation:

$$a_t = \phi_{1,t} + \phi_{2,t} \tag{6}$$

where $\phi_{1,t}$ and $\phi_{2,t}$ represent planned and autonomous adaptation, respectively, and are expressed in °C. Autonomous adaptation is not a conscious response to climate change, but a spontaneous and reactive reaction to changes in natural and human systems and the costs of these actions are private. On the contrary, planned adaptation is the result of a deliberate policy or investment decision to respond to observed and/or projected changes in climate (IPCC, 2007; Neumann and Strzepek, 2014; Fankhauser et al., 1999).

Two possible specifications are proposed for autonomous adaptation:

$$\phi_{2,t} = T_t e^{-kT_t} \tag{7a}$$

and

$$\phi_{2,t} = T_t e^{-k(T_t - \phi_{1,t})} \tag{7b}$$

where $k > 0$ is a parameter that determines the fraction of the increase in T_t that can be absorbed by autonomous adaptation. As is shown in Figure A1, this fraction is a decreasing function of k and $T_t > 0$.[4] k also controls at which temperature change level the maximum adaptation occurs, namely $1/k$. This specification assumes that private adaptation costs increase with T_t and that as the system gets increasingly stressed due to the changes in climate, its capacity to respond autonomously to additional increases in T_t is reduced. For instance, a farmer is likely to unconsciously adapt to small levels of warming through gradual changes in crop management. But this approach becomes less effective when climate change becomes larger and the need for planned adaptation increases, for example, by introducing irrigation and growing different crop types. Note that these additional increases in T_t do not undo the adaptation that occurred in previous periods. For small changes in climate, the value of the exponential weighting function in these equations is close to 1 and therefore $\phi_{2,t} \approx T_t$. However, as T_t increases, the capacity of the system to adapt in an autonomous way decreases. Note that other more complex functions, such as the Gamma distribution, could be used for this purpose. Here, for the sake of simplicity, we use an exponential function which has only one parameter. By varying the values of k, the proposed specification allows to represent a wide range of autonomous adaptation capacity. Due to the lack of information about aggregate autonomous adaptation at the global scale, this parameter cannot be fitted. Therefore, we arbitrarily set $k = 1$ for the results presented in the next sections and we provide a sensitivity analysis in section 2 of the Supplementary Information to illustrate the flexibility of the proposed specification.[5] Equation (7b) allows for synergistic effects between planned and autonomous adaptation by reducing the rate at which autonomous adaptation decreases with increases in T_t. This implies that the maximum possible autonomous adaptation also depends on the level of planned adaptation. The rationale behind Equation (7b) is that planned adaptation is likely to provide favorable conditions for further autonomous adaptation to take place.

Whereas autonomous adaptation is not a decision variable, planned adaptation is chosen, and that choice requires investment. As such $\phi_{1,t}$ is the policy variable of interest and we focus on planned adaptation costs. Note that the proposed framework could be extended in future research to include autonomous adaptation costs as well. However, this represents a major challenge since the available estimates about global adaptation costs are primarily about planned adaptation, due to the difficulty of identifying and costing the enormous range of actions that could be considered autonomous adaptation (Parry et al., 2009; Narain et al., 2011; Fankhauser et al., 2016). As in previous studies (De Bruin et al., 2009a; De Bruin et al., 2009b), planned adaptation costs (AD_t) are assumed to be a power function of $\phi_{1,t}$:

$$AD_t = \lambda_1 \phi_{1,t}^{\lambda_2} \tag{8}$$

The intuition behind this specification is that adaptation costs increase non-linearly with the level of adaptation implemented when $\lambda_2 > 1$, which implies increasing marginal adaptation costs.

In the Supplementary Information section1 we derive the optimality conditions of the proposed damage function, assuming a constant coping range and for three cases of autonomous adaptation: 1) no autonomous adaptation; 2) independent planned and autonomous adaptation and; 3) synergistic effects between planned and autonomous adaptation. The optimization problem consists in maximizing the net benefits NB of planned adaptation, i.e., the difference in damages between the cases of no adaptations and with adaptation, minus the costs of adaptation, at time t:

$$\begin{aligned} NB_t &= D_t(T_t) - D_t^{ad}(T_t, a_t) - AD_t \\ &= \beta_1 T_t + \beta_2 T_t^{\alpha_3} - [\beta_1(T_t - a_t) + \beta_2(T_t - a_t)^{\alpha_3}] - \lambda_1 \phi_{1,t}^{\lambda_2} \end{aligned} \tag{9}$$

where $\beta_1 = \frac{\alpha_1}{\sigma}$, $\beta_2 = \frac{\alpha_2}{\sigma^{\alpha_3}}$. There is no analytical solution to the first-order conditions in equation (A2) to A4, unless we impose restrictions on

[2] For the ease of exposition and without loss in generality, we assume that deviations with respect to the optimal climate generate negative impacts and that the impacts under the optimum temperature are zero. Note that any power or polynomial function can be shifted in this way by adding a constant.

[3] This approach follows the common practice in IAMs of economic impacts from climate change to represent global and regional impacts as a function of temperature (Nordhaus, 2010). This function is a simplification because changes in other climate variables like precipitation and sea level rise are expected to determine local impacts.

[4] To allow for negative temperature changes $T_t e^{-|\cdot|}$ can be used, but this is not relevant for our application of global warming in which temperature is projected to increase with respect to a base year.

[5] Our specification implies that even for larger changes in temperature, autonomous adaptation can still take place, but at a lower rate when temperature increases. The reason is that there are economic and physical limits to adaptation. This can be interpreted as an analogy to the common expectation that the marginal benefits of adaptation decline when a lot of adaptation has already taken place. An opposite result may occur when adaptation suddenly increases rapidly in response to large and rapid climate changes. Such a specification can be relevant for future research.

parameters. We therefore numerically solve for the optimal level of planned adaptation. Figure A2 illustrates optimal adaptation levels for the three cases above, highlighting the interaction between autonomous and planned adaptation. If autonomous and planned adaptation are independent, autonomous adaptation reduces optimal planned adaptation. However, with synergies between the two types of adaptation, for moderate to high warming, the optimal level of planned adaptation is higher if autonomous adaptation is included. Note that in practice optimality of adaptation policies may be difficult to obtain. Our proposed damage function can be used for optimal adaptation as well as for *what-if* scenarios (Füssel, 2010) which are useful to explore the implications of non-optimal policies that decision makers may consider implementing.

Adaptation can be reactive or anticipatory (Fankhauser et al., 1999). In Equation (A1) to (A4), adaptation can be either reactive or anticipatory (see Supplementary Information, section 1). The numerical example in section 3 optimizes planned adaptation, maximizing the present value of the natural logarithm of GDP per capita over 100 years. This is consistent with IAMs that explore optimal climate policy. In this example, adaptation is anticipatory since it considers the evolution of impacts during a century into the future.

2.2. Specification of the coping range in the damage function

The coping range defines the interval within which variations in climate conditions do not cause significant impacts to a system due to its underlying resilience (see Yohe and Tol, 2002; Downing et al., 1997). The coping range is not necessarily constant, and therefore the same climate shock can cause different impacts depending on the state of the system. Moreover, significant and/or sustained impacts to the system can decrease its resilience and capacity to cope in the following periods. The dynamics of the coping range can be represented as follows:

$$\sigma_t = \mu + \rho\sigma_{t-1} - D_{t-1}^{ad}\sigma_{t-1} = \mu + \rho_t^{*}\sigma_{t-1} \tag{10}$$

for $t = 1, ..., T$, where ρ is the momentum of the coping range and $\rho^{*} = \rho - D_{t-1}^{ad}$ is that momentum adjusted for past impact. Here $\mu = (1-\rho)\sigma^{*}$ is the constant that represents the coping range of the system without climate change, and σ^{*} is the long-run coping range value without climate change. The objective of this equation is to incorporate dynamics into the damage function by taking into account the effects of current and past impacts over the ability of society to cope with further damages. This allows to make impacts and sensitivity time- and path-dependent. Here, for simplicity, these effects are accounted by a one-lag memory term. However, other more complex representations, such as longer lags or asymmetric functions, could be adopted.

Note that in equation (10), σ_t depends on a_{t-1} via D_{t-1}^{ad} but it is independent from a_t, which means that the current coping range depends on past adaptation only. Equation (10) is quasilinear in σ_{t-1}. Equation (10) can be rewritten as:

$$\sigma_t = (1-\rho)\sigma^{*} + \rho_t^{*}\sigma_{t-1} \tag{11}$$

which shows that the coping range at time *t* is a sum of the undisturbed coping range and the coping range at time *t-1*, weighted by $(1-\rho)$ and ρ_t^{*}. Under stationary climate conditions $\sigma_t = \sigma^{*}$. However, under changing climate conditions D_{t-1}^{ad} will be systematically different from zero and the coping range will decrease/increase as the impacts of climate change become more negative/positive. This implies that the sensitivity of the system —represented by the parameters in Equation (4)— will change accordingly to reflect the time-evolving coping capacity of the system. In addition, the effects of D_{t-1}^{ad} on σ_t are persistent and even when the direct impacts of climate change have stopped, the system will only go back to its original state after a certain period of time. Note that equation (10) can be seen as a first order difference equation of the type $z_t = b + \rho z_{t-1} + e_t$ with forcing process $e_t = D_{t-1}^{ad}\sigma_{t-1}$. As such, the effects of a one-time shock on σ_t will be more persistent as ρ approaches 1.

While σ^{*} is a description of the initial state of the system's vulnerability, σ_t is determined in part by, a_{t-1}, that is by the autonomous adaptation and the investment done in planned adaptation. The effects of adaptation over the coping range are described in section 3 of the Supplementary Information.

3. Generalizing the DICE and AD-DICE damage functions to include dynamic coping ranges and adaptation

3.1. Standard damage functions and fitting of the proposed damage function

The proposed damage function is based on that of the DICE model, in particular on the AD-DICE2007 extension. As described below, the new damage function is parameterized to approximate the results of that of the AD-DICE2007, for the base case of the static coping range.

The DICE damage function (Nordhaus and Boyer, 2000; Nordhaus, 2008) expresses damages in terms of changes in global temperature from its 1900 value, which is chosen to represent the pre-industrial climate. We use the ensemble median of global mean surface temperatures from the HadCRUT4 dataset[6] to characterize this baseline climate (Morice et al., 2012). The HadCRUT4 is a 5°x5° gridded monthly surface temperature dataset available from January 1850 until present day. The parameter values for DICE99, DICE2007 and two versions of AD-DICE2007 (gross damage) are shown in Table 1. We modified AD-DICE2007 by setting the $\alpha_3 = 2$, as in DICE, instead of the fractional coefficient originally proposed. Parameters α_1 and α_2 for this function (Table 1) are obtained by minimizing the sum of square differences between the original AD-DICE2007 and modified AD-DICE2007* functions for a range of 0 °C to 6 °C temperature increase ($R^2 = 0.997$, from a regression between the original AD-DICE2007 and the modified AD-DICE2007* damage functions). The main difference between the DICE and AD-DICE2007 damage functions is that the first is fitted to represent expected impacts after "optimal adaptation", while that of the AD-DICE2007 is fitted to reproduce the implied total damages (i.e., the impacts after adaptation plus adaptation costs) of the DICE model.

Equation (4) is a parabola, as is the DICE damage function. Parameters are readily matched:

$$D_t^{ad} = \alpha_1\sigma^{*}S_t + \alpha_2(\sigma^{*})^2S_t^2 = \alpha_1^{cr}S_t + \alpha_2^{cr}S_t^2 \tag{14}$$

where $\alpha_1^{cr} = \alpha_1\sigma^{*}$ and $\alpha_2^{cr} = \alpha_2(\sigma^{*})^2$. In other words, parameters α_1^{cr} and α_2^{cr} allow to exactly match the projected losses in GDP using variable S_t that would be obtained using the original DICE parameters and variable T_t. For this adjustment, an estimate of the coping range is needed. One possibility is to choose σ^{*} such that the world was nearly completely adapted to the pre-industrial climate by year 1900, although this might be an overly optimistic assumption. Nevertheless, this is consistent with the standard DICE model damage function assuming that climate change impacts are zero in 1900. As such, we assume that the coping range corresponds to 3 standard deviations of global temperatures estimated from a 31-year period centered in 1900.[7] The coping range is $\sigma^{*} = 0.345$ °C and the fitted parameters are shown in Table 1. Note that

[6] At the time of writing this paper the latest HadCRUT4 dataset was version HadCRUT.4.2.0.0. The differences between this version of the dataset and the latest one regarding the standard deviations of global mean temperatures used in this paper are negligible. The differences in these standard deviations are −0.002 °C and 0.003 °C for the 31-year period centered in year 1900 and for the whole dataset, respectively. Data are available at: http://www.metoffice.gov.uk/hadobs/hadcrut4/data/4.2.0.0/time_series/HadCRUT.4.2.0.0.annual_ns_avg.txt.

[7] Global temperature during the selected period can be represented by a Normal distribution (Jarque-Bera statistic 1.93). An interval of three standard deviations from the mean covers about 99.7% of the probability mass of this distribution.

Table 1
Parameter values of the damage functions in the original and modified DICE99 and DICE2007 models (equation (1)).

Model	α_1	α_2	α_1^{cr}	α_2^{cr}	α_3
DICE99	−0.00450	0.00350	−0.00155	0.00042	2
DICE2007	0.00000	0.00284	0.00000	0.00034	2
AD-DICE2007 (Gross damage)	0.0004	0.0027	0.00014	0.00025	2.243
AD-DICE2007* (Gross damage)	–	–	0.00000	0.00057	2

Note: AD-DICE2007* is the approximation of the original AD-DICE2007, restricting the power coefficient to be equal to 2. α_1^{cr} and α_2^{cr} are constant parameters fitted by the coping range.

the magnitude of σ^* is deceivingly small. Such value at the global scale can imply much larger variability at regional and local scales and therefore a coping range of 0.345 °C can be indeed large for the world's societies and natural systems as a whole (Figure A3). Note, however, that the damages obtained from Equation (14) do not depend on the initial value chosen for the coping range, but on the ratio between this value and the value of the coping range at time t.

Nevertheless, the value for coping range σ^* is important to estimate how extreme a given level of warming is with respect to what a system has previously experienced. Table 2 shows what increases up to 6 °C in global temperature represent in coping range units and the corresponding expected economic impacts according to the DICE models. Making an analogy with statistical concepts helps illustrating the magnitude of the projected changes. Assume the coping range to be the standard deviation of a Normal distribution. A three-standard deviation change in the mean conditions would take the system out of a large part of what it had previously experienced, and for a six-standard deviation change there would be virtually no overlap between the past and future probability distributions.

As shown in Table 2, a near six σ^* change would occur for a 2 °C increase in T_t and a 6 °C change would entail taking the system out of its normal conditions by more than 17 times σ^*. The corresponding economic impacts projected by the DICE99 and DICE2007 models are about 0.5% (1.14%) and 9.9% (10.22%) of GDP for a 2 °C and 6 °C warming, respectively. For the AD-DICE2007 and modified AD-DICE2007 these impacts are about 1.36% (1.92%) and 15.26% (17.26%) of GDP, respectively, for a 2 °C and 6 °C warming respectively. It is hard to imagine any natural or social system that, when taken so far outside the set of conditions it has ever experienced, would suffer so little damage. As such, Table 2 suggests that, as has been previously pointed out (Weitzman, 2012), these damage functions may importantly underestimate the potential damages of climate change, particularly for large increases in T_t. As shown by the numbers in brackets in Table 2, these arguments hold even when a much larger value for the coping range is chosen ($\sigma^* = 0.806$), which represents three standard deviations of T_t estimated using the whole sample period 1850–2010).

3.2. Generalized damage function that accounts for the dynamics of planned adaptation and sensitivity of the system affected by climate change

The planned adaptation costs function in Equation (8) was fitted by minimizing the sum of the square differences between the original costs function (De Bruin et al., 2009a) and Equation (8). Following de Bruin, De Bruin et al., 2009b, the point chosen for which the two models are identical, was 2.4 °C increase over the reference climatology centered in 1900. The parameter values for Equation (8) then are $\lambda_1 = 11.712$ and $\lambda_2 = 4$. As shown in Figure A4, the costs of planned adaptation to completely adapt to small changes in T_t are very low but rapidly accelerate when fully adapting to larger values of T_t, reaching 1% of GDP for about 0.55 °C and about 11.7% for 1 °C.

To illustrate the implications of the proposed generalized damage function for the economic impacts of climate change, we use two climate change scenarios consisting in linear increases in global temperature of 2 °C and 6 °C, respectively, in 100 years. These scenarios cover a wide uncertainty range in global temperature projections: the higher warming scenario leads to a temperature increase by the end of the century similar to that of an unabated, high greenhouse gases emissions scenario and a high climate sensitivity; the lower warming scenario could represent an ambitious global mitigation scenario broadly similar to the Paris Climate Agreement that aims to keep temperature increase at 2 °C by the end of the century. The linear increase in warming is chosen to investigate the behavior of the proposed damage function without the influence of nonlinearities in temperature projections. For these examples, world GDP is assumed to grow exponentially at a 2% rate. To obtain the optimal adaptation effort, an optimization procedure for maximizing the present value of the natural logarithm of GDP (constant relative risk aversion; 4% discount rate) was applied. The coping range dynamic Equation (11) is parameterized to represent two different cases: low ($\rho = 0$) and high ($\rho = 0.5$) sensitivities.

First we discuss the case of no autonomous adaptation ($a_t = \phi_{1,t}$). Fig. 1 compares the economic impacts as percent of global GDP obtained from the modified AD-DICE2007 damage function to those from the generalized damage function described in the previous section. Panels a) and b) show that for moderate changes in T_t (i.e., 2 °C), the projected impacts from the proposed damage function are almost the same as those of the AD-DICE2007 (i.e., show a similar quadratic-type behavior), irrespective of the sensitivity of the coping range is low or high. The optimal adaptation produces important reductions in damages of almost one-quarter of the expected gross impacts and leads to values closer to the original DICE2007 "optimal adaptation" function. However, due to the inclusion of sensitivity and adaptation dynamics, for increasing levels of warming these functions diverge, even when adaptation is included. For up to 1 °C global temperature increase, the residual damages plus adaptation costs obtained from the proposed damage function are very similar to those from DICE2007. However, these damage functions diverge for higher levels of warming. For example, for a 1 °C warming and for the case of high sensitivity and planned adaptation, the difference between the proposed and the DICE2007 functions is −0.03% of GDP, while for 2 °C the difference increases to −0.41% (Fig. 1b).

Table 2
Projected impacts for global temperature increases from 0 °C to 6 °C in percentage of GDP for different damage functions.

T_t (°C)	T_t (σ^*)	DICE99	DICE2007	AD-DICE2007 (Gross damage)	AD-DICE2007* (Gross damage)
0	0	0	0	0	0
1	2.90 [1.24]	0.10	−0.28	−0.31	−0.48
2	5.80 [2.48]	−0.50	−1.14	−1.36	−1.92
3	8.70 [3.72]	−1.80	−2.56	−3.29	−4.31
4	11.59 [4.97]	−3.80	−4.54	−6.21	−7.67
5	14.49 [6.21]	−6.50	−7.10	−10.18	−11.98
6	17.39 [7.45]	−9.90	−10.22	−15.26	−17.26

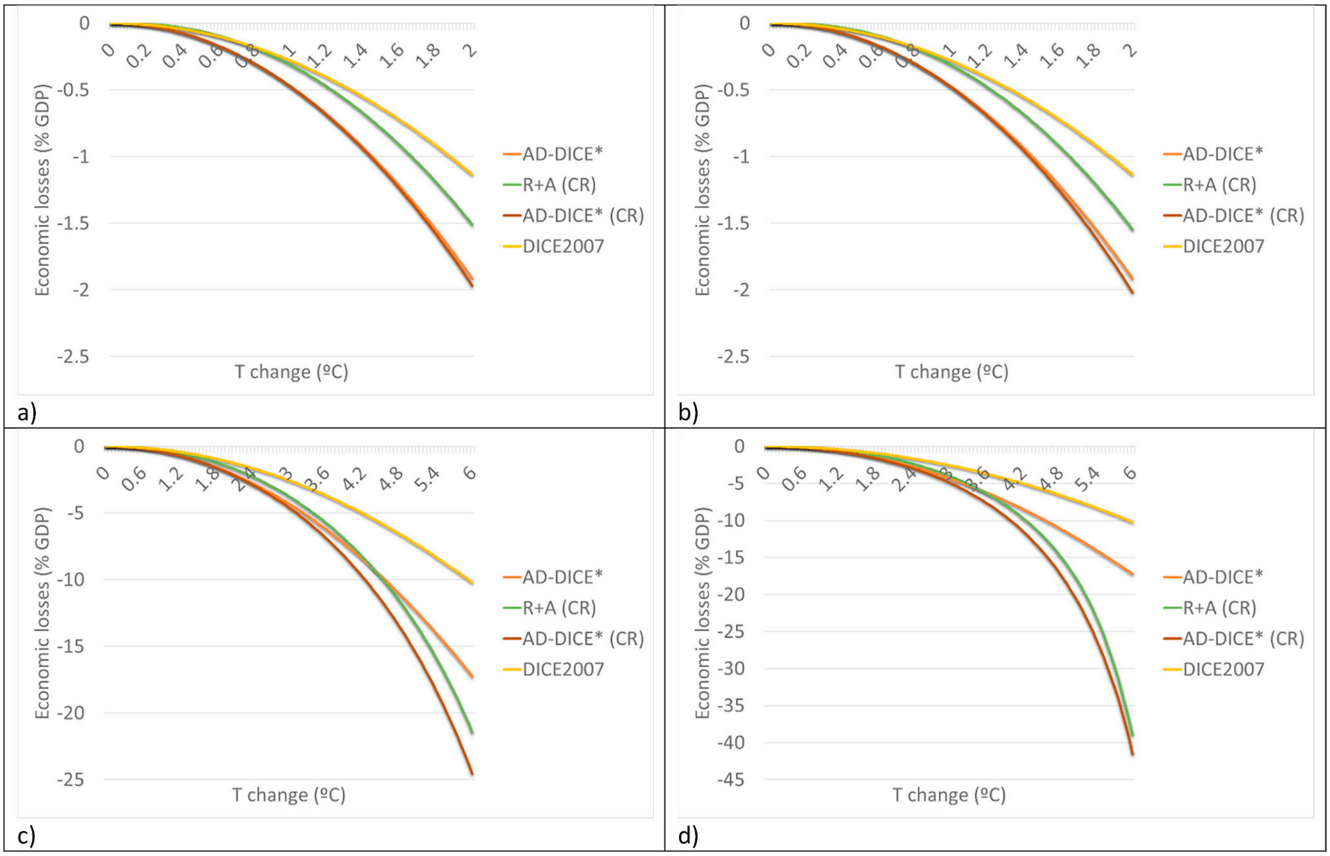

Fig. 1. Economic losses as percent of global Gross Domestic Product (GDP). Panels a) and b) show the projected losses for a temperature change T_t=2 °C for low (ρ = 0) and high (ρ = 0.5) sensitivity to changes in temperature, respectively. Panels c) and d) show the projected losses for T_t= 6 °C for low (ρ = 0) and high (ρ = 0.5) sensitivity, respectively. AD-DICE*, R + A (CR), AD-DICE* (CR), and DICE2007 represent the gross damage from the modified AD-DICE damage function, the residual and adaptation costs using a dynamic coping range, the AD-DICE gross damage using a dynamic coping range, and the damages from the DICE2007 damage function, respectively.

Divergence for increasing levels of warming also occurs between the proposed function and the AD-DICE2007 function, even when optimal adaptation is included. For large increases in temperature (Fig. 1 panels c and d) the projected impacts from the generalized damage function are highly nonlinear and very different to those of the AD-DICE2007. The sensitivity of the coping range has a large impact on the percent of GDP loss. In fact, Fig. 1d shows damages comparable to those in Weitzman, (2012) but in this case arising as a consequence of past climate change impacts over the coping capacity of the system. These results are also similar to those presented in Estrada et al. (2015), which uses an empirical approach to account for impact dynamics and persistence.

The optimal adaptation level and the corresponding costs for the different climate scenarios and sensitivities are shown in Fig. 2 panels a) and b). These panels illustrate how for large changes in T_t the sensitivity of the coping range can introduce large nonlinearities to the optimal adaptation path and its costs, while for small changes in climate the differences between high and low sensitivity estimates are negligible. The costs of adaptation for the 2 °C temperature scenario increase slowly and reach about one tenth of percent of global GDP at

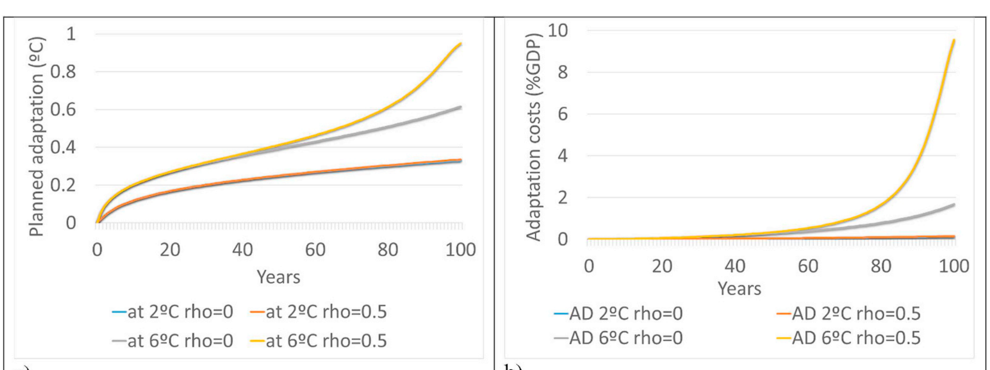

Fig. 2. Panel a) adaptation level a_t for $T_t = 2°C$, low and high sensitivity to changes in temperature (blue and red lines, respectively) and temperature change $T_t = 6°C$, low (ρ = 0) and high (ρ = 0.5) sensitivity (grey and yellow lines, respectively). Panel b) adaptation costs AD_t (equation (8)) for $T_t = 2°C$, low (ρ = 0) and high (ρ = 0.5) sensitivity (blue and red lines, respectively) and $T_t = 6°C$, low (ρ = 0) and high (ρ = 0.5) sensitivity (grey and yellow lines, respectively). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the end of the century, irrespective if a low or high sensitivity is chosen. However, the differences in adaptation costs from low to high sensitivities under the more extreme climate change scenario are very large, representing more than 7% of GDP. For this high sensitivity scenario, at the end of the current century GDP almost stops growing even if the optimal levels of adaptation are implemented (Figure A5).

3.3. Generalized damage function that accounts for autonomous adaptation, and its synergy with planned adaptation

We now turn to the cases in which autonomous adaptation is included by means of Equations (7a) and (7b). Results are based on the same climate scenarios described above and high sensitivity in the coping range specification ($\rho = 0.5$). Under a moderate warming scenario (Fig. 3a), the introduction of autonomous adaptation leads to economic impacts around 0.10% of GDP until half of the century (i.e., 1 °C warming), representing a 66% decrease in losses with only planned adaptation. The combination of planned and autonomous adaptation brings down the costs of climate change at the end of the century from 2% under the no adaptation scenario to about 1% of GDP.

Throughout the century, the synergistic effects between autonomous and planned adaptation are positive and lead to total adaptation levels much higher than those attained only with planned adaptation alone and higher than those obtained with independent autonomous and planned adaptation (Fig. 3d). In general, autonomous adaptation reduces the optimal level of planned adaptation and the associated costs (Fig. 3b and c). In the case when synergistic effects are taken into account, the optimal planned adaptation level is low for the first half of the century, but it increases rapidly afterwards. At the end of the century, the planned adaptation attains higher levels than when autonomous adaptation is ignored. In this case, the optimal investment in adaptation at the end of the century is higher than in any other case. This is due to the assumption that synergistic effects expand the range of autonomous adaptation when planned adaptation increases, making adaptation cheaper.

Fig. 4 shows that the effects of autonomous adaptation (whether synergistic effects are taken into account or not) are limited for higher warming scenarios. In other words, adaptation takes place for a small fraction of the total temperature rise. The differences in the total level of adaptation (Fig. 4d) between planned, planned and autonomous, and planned and autonomous with synergistic effects start decreasing for warming above 1.5 °C (year 25). For increases in T_t larger than 5 °C (from year 84 onwards), the total adaptation depends mostly on the chosen planned adaptation level (Fig. 4c). The largest differences in adaptation costs due to inclusion of autonomous adaptation occur at the end of the century and when synergistic effects are allowed (about 0.5% of GDP). Results suggest that the most important contribution of autonomous adaptation is restricted to moderate warming. For larger increases in T_t, the gains from autonomous adaptation in terms of avoided impacts are small. While there may be limits to adaptation, we are not explicitly accounting for this. Nevertheless, adaptation is limited to only a decreasing fraction of the increases in T_t due in part to the rapidly increasing costs of adaptation. In the numerical example in Fig. 4, for small increases in T_t, the total adaptation level is close to

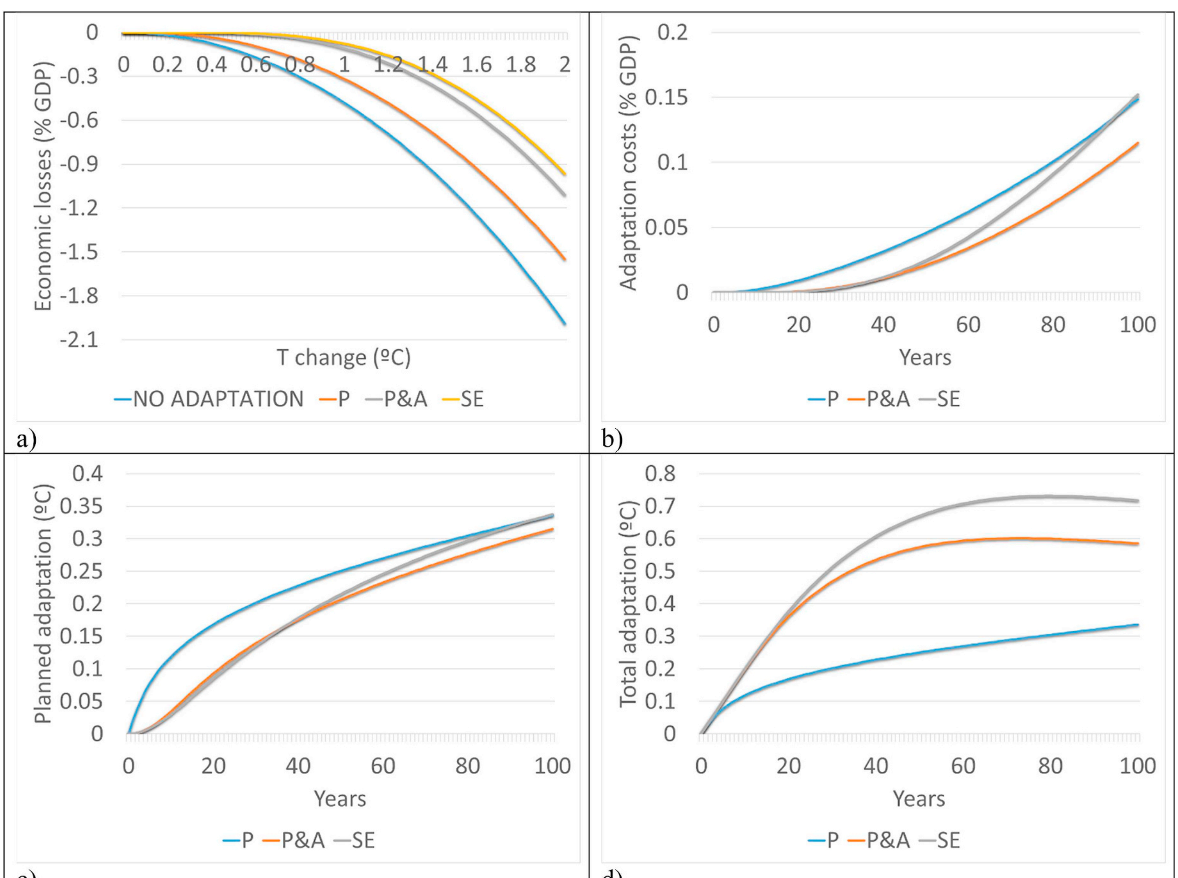

Fig. 3. Effects of autonomous adaptation on economic losses, adaptation levels and costs for temperature change $T_t = 2°C$ and high sensitivity (ρ = 0.5) to changes in temperature. Panel a) economic losses as percent of global GDP for the following cases: no adaptation (blue), planned adaptation (red; P), planned and autonomous adaptation (grey; P & A), and synergistic effects (yellow; SE). Panel b) adaptation costs AD_t for P (blue), P & A (red) and SE (grey). Panel c) planned adaptation for P (blue), P & A (red) and SE (grey). Panel d). total adaptation level a_t for P (blue), P & A (red) and SE (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

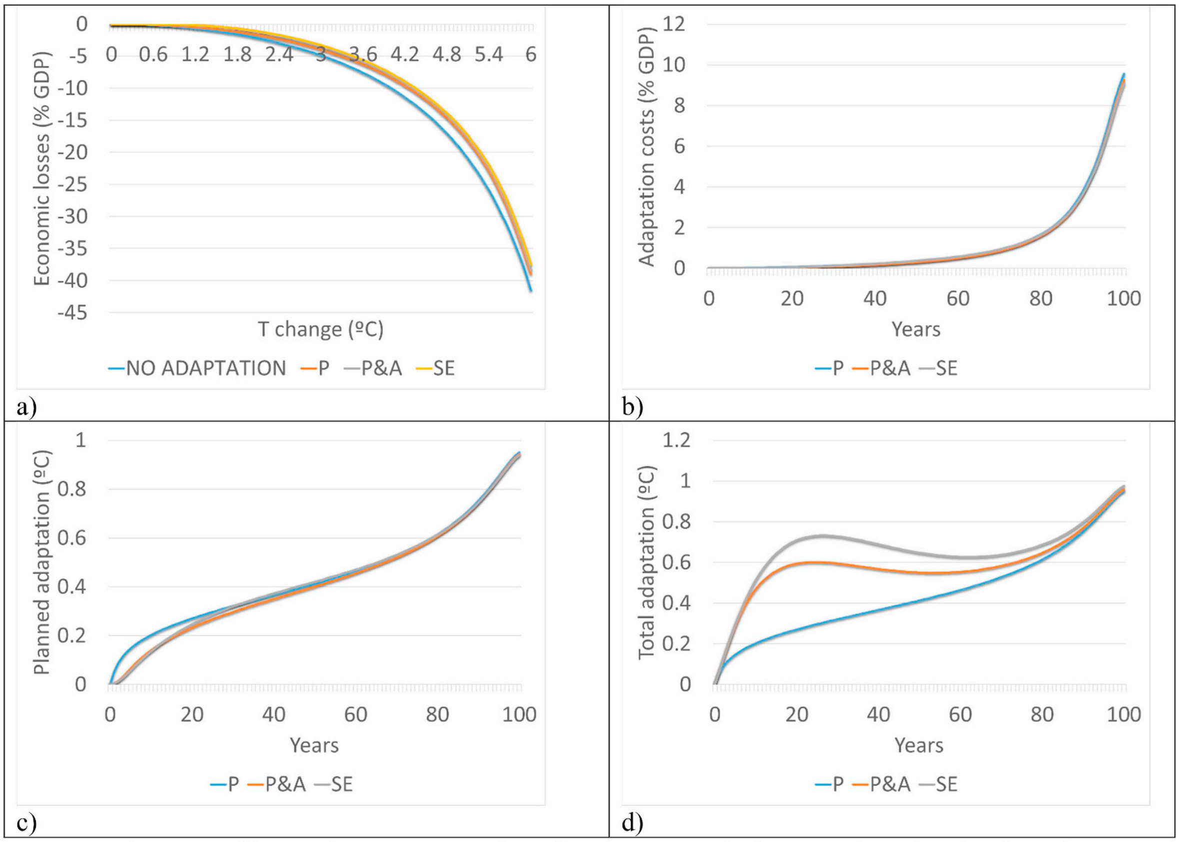

Fig. 4. Effects of autonomous adaptation on economic losses, adaptation levels and costs for temperature change $T_t = 6°C$ and high sensitivity (ρ = 0.5) to changes in temperature. Panel a) economic losses as percent of global GDP for the following cases: no adaptation (blue), planned adaptation (red; P), planned and autonomous adaptation (grey; P & A), and synergistic effects (yellow; SE). Panel b) adaptation costs AD_t for P (blue), P & A (red) and SE (grey). Panel c) planned adaptation for P (blue), P & A (red) and SE (grey). Panel d) total adaptation level a_t for P (blue), P & A (red) and SE (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

100% of temperature change, but this fraction decreases rapidly and reaches about 16% for high warming values (e.g., 6 °C). This decrease is faster when no autonomous adaptation is considered and much slower when synergistic effects between planned and autonomous adaptation is allowed.

It is important to take into account that the interaction between adaptation and mitigation decisions is not considered here. The interest of the present paper is to focus on the behavior of the proposed damage function, not a full IAM. As such, mitigation (and its interaction with adaptation) is outside the scope of the present analysis.

3.4. Discussion of main assumptions and limitations of IAMs

The key assumptions with critical implications for IAM outputs can be ranked as follows. As has been discussed previously in the literature, the weakest part in IAMs are their damage functions and their ability to adequately represent climate change impacts, adaptation and vulnerability processes (Füssel, 2010; Nordhaus, 2011; Burke et al., 2016; National Academies of Sciences Engineering and Medicine, 2017). The empirical basis available to specify and fit such functions is small and a variety of aspects of natural and human systems are poorly represented or omitted (van den Bergh and Botzen, 2014). Moreover, most of the available damage functions are static, and as such imply that human and natural systems are characterized by unrealistic levels of resilience (Tol and Fankhauser, 1998; Estrada et al., 2015). As argued in this paper, the ability to cope with climate change impacts is a function of the state of the system that is not fixed, and a more realistic representation of it as a dynamic process would lead to significantly different outcomes in IAMs. Similarly, adaptation capacity, costs and modeling are poorly known and represented, but adaptation can have large effects on the costs estimates of IAMs and on policy recommendations (Kurukulasuriya et al., 2006; Kahn, 2016; Costinot et al., 2016). Recent literature has underlined the importance of geographical resolution in IAMs, showing that modelling local-scale impacts and adaptation can significantly change the aggregated costs of climate change at the regional level and global scales (Füssel, 2010; Estrada et al., 2017a,b). Moreover, increasing our understanding and modeling of uncertainty in climate projections and about possible large-scale climate catastrophes could substantially modify the projected impacts of climate change over the next few centuries (Weitzman, 2009; Diaz and Moore, 2017). Different assumptions for projecting economic growth have large implications about future climate change impacts and what optimal climate policies would be (Tol, 2018). Choosing the discount rate is one of the most discussed topics in this field and it is known to have large effects on IAMs outcomes, and there is debate about its appropriate value (Arrow et al., 2013).

The field of climate change economics deals with the study of a variety of natural and human complex systems and their interactions. The knowledge and information about these systems and how they could respond to external changes is, by definition, fragmented and limited. As such, the capacity to model such systems and to project how they would evolve in the future under different development paths is necessarily associated with epistemic uncertainty, critical assumptions, simplifications and omissions as well as subjective constructs (Estrada et al., 2017a,b). Furthermore, validation and verification of models of complex systems is problematic (Oreskes et al., 1994) and, in the case of climate-economy IAMs, there is no observed data of welfare impacts of climate change to compare with. However, most of these problems are not exclusive to climate change economics or IAMs, but common to most of the impact, vulnerability and adaptation studies, and in some respects even to climate modeling. As is suggested in the previous sections, important progress in the climate change impact, adaptation and vulnerability assessment field would be to make the underlying assumptions and limitations explicit and more visible and readily known to the readers and policy makers.

4. Conclusions

While a limited number of damage functions for IAMs explicitly model adaptation, the dynamic links between impacts, adaptation efforts and the system's sensitivity has been seldom explored or modelled. In this paper, we examined the question which kind of damage function is suitable for accounting for such dynamics? We presented a generalized damage function that allows feedbacks and interactions between impacts, autonomous and planed adaptation and vulnerability by explicitly modeling adaptation and sensitivity as dynamic processes. The proposed generalizations not only can emulate the behavior of the damage functions included in some of the most commonly used IAMs but, through dynamic sensitivity, it provides a mechanism for the type of highly nonlinear impacts for large changes in climate that has been recently discussed in the literature (Weitzman, 2012; Dietz, 2011; Ackerman et al., 2010). The second research questions we examined was what are the implications of using the proposed damage function for assessing the economic impacts of climate change? In most of previous studies, large damages for high levels of warming are produced by assuming highly nonlinear functional forms. In the damage function proposed in this paper, large economic damages occur as a consequence of the effects of past climate impacts on the capacity of the affected system to cope with further warming. Contrary to most of the current damage functions, this new type of damage function maps economic losses in terms of the time-varying capacity of a system to deal with climate conditions experienced at a certain period in time, instead of fixed proportional damages produced by absolute changes in climate.

The type of damage function presented in this paper can be extended in several directions. The ones we believe to be more relevant are:

- A general challenge with climate change damage functions that also applies to the one proposed in this study is the empirical fit of its parameter values in the absence of observed data on climate impacts and adaptation (Dell et al., 2014; Diaz and Moore, 2017). An important topic for future research is to examine how empirically adjusted damage functions can be estimated that account for dynamics in adaptation and sensitivity of the system affected by climate change.
- The effects of economic development on vulnerability are important determinants of the impacts that will be experienced under climate change conditions (e.g., Tol, 2018). An interesting extension of the proposed damage function would be to include in the coping range equation how changes in development can increase/reduce the range to which society is resilient to climate.
- Different types of limits to adaptation are expected to exist (physical, social, technological and economic, among others; e.g., Adger et al., 2009). The current specification of adaptation does not consider these limits, and only evaluates the economic convenience of different planned adaptation levels. Estimating such limits to adaptation at the aggregate level and for global/regional scales is challenging, but needed to have a better understanding of adaptation in the context of economic IAMs.
- The analysis of the inter-relationships between adaptation and mitigation for optimal climate policy under different emissions scenarios. For some ranges of implementation levels and warming, mitigation and adaptation can be either complementary or substitute and important synergies and/or trade-offs can be present (e.g., Klein et al., 2007). Additionally, optimal levels of mitigation, and adaptation are expected to be considerably affected by different assumptions regarding discount rates and utility function specifications.

Acknowledgements

Francisco Estrada acknowledges financial support for this work from the Consejo Nacional de Ciencia y Tecnología (http://www.conacyt.gob.mx) under grant CONACYT-310026, as well as from PASPA-DGAPA of the Universidad Nacional Autónoma de México. Wouter Botzen has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 776479.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2019.104504.

References

Arrow, K., Cropper, M., Gollier, C., Groom, B., Heal, G., Newell, R., Nordhaus, W., Pindyck, R., Pizer, W., Portney, P., Sterner, T., Tol, R.S.J., Weitzman, M., 2013. Determining benefits and costs for future generations. Science 341, 349–350. https://doi.org/10.1126/science.1235665.

Ackerman, F., Stanton, E.A., Bueno, R., 2010. Fat tails, exponents, extreme uncertainty: simulating catastrophe in DICE. Ecol. Econ. 69 (8), 1657–1665.

Adger, W.N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D.R., Naess, L.O., Wolf, J., Wreford, A., 2009. Are there social limits to adaptation to climate change? Clim. Change 93 (3), 335–354.

Akhtar, M.K., Wibe, J., Simonovic, S.P., MacGee, J., 2013. Integrated assessment model of society-biosphere-climate-economy-energy system. Environ. Model. Softw 49, 1–21.

Baumberger, C., Knutti, R., Hirsch Hadorn, G., 2017. Building confidence in climate model projections: an analysis of inferences from fit. Wiley Interdiscip. Rev.: Clim. Change 8. https://doi.org/10.1002/wcc.454.

Bosello, F., De Cian, E., 2014. Documentation on the development of damage functions and adaptation in the WITCH model. CMSS Research Papers Issue RP0228. http://www.cmcc.it/wp-content/uploads/2014/11/rp0228-cip-10-2014.pdf.

Botzen, W.J.W., van den Bergh, J.C.J.M., Chichilnisky, G., 2018. Climate policy without intertemporal dictatorship: chichilnisky criterion vs. Classical utilitarianism in DICE. Clim. Change Econ. 9 (2), 1–17.

Burke, M., Craxton, M., Kolstad, C.D., Onda, C., Allcott, H., Baker, E., Barrage, L., Carson, R., Gillingham, K., Graf-Zivin, J., Greenstone, M., Hallegatte, S., Hanemann, W.M., Heal, G., Hsiang, S., Jones, B., Kelly, D.L., Kopp, R., Kotchen, M., Mendelsohn, R., Meng, K., Metcalf, G., Moreno-Cruz, J., Pindyck, R., Rose, S., Rudik, I., Stock, J., Tol, R.S.J., 2016. Opportunities for advances in climate change economics. Science 352, 292–293. https://doi.org/10.1126/science.aad9634.

Butler, M.P., Reed, P.M., Fisher-Vanden, K., Keller, K., Wagener, T., 2014. Identifying parametric controls and dependencies in integrated assessment models using global sensitivity analysis. Environ. Model. Softw 59, 10–29.

Costinot, A., Donaldson, D., Smith, C., 2016. Evolving comparative advantage and the impact of climate change in agricultural markets: evidence from 1.7 million fields around the world. J. Political Econ. 124, 205–248. https://doi.org/10.1086/684719.

De Bruin, K., Dellink, R., Tol, R.S.J., 2009a. AD-DICE: an implementation of adaptation in the DICE model. Clim. Change 95 (1–2), 63–81.

De Bruin, K., Dellink, R., Agrawala, S., 2009b. Economic Aspects of Adaptation to Climate Change. OECD Environment Working Papers. Organisation for Economic Co-operation and Development, Paris. http://www.oecd-ilibrary.org/content/workingpaper/225282538105.

de Vos, M.G., Janssen, P.H.M., Kok, M.T.J., Frantzi, S., Dellas, E., Pattberg, P., Petersen, A.C., Biermann, F., 2013. Formalizing knowledge on international environmental regimes: a first step towards integrating political science in integrated assessments of global environmental change. Environ. Model. Softw 44, 101–112.

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the Weather? The new climate–economy literature. J. Econ. Lit. 52, 740–798.

Diaz, D., Moore, F., 2017. Quantifying the economic risks of climate change. Nat. Clim. Chang. 7, 774–782.

Dietz, S., 2011. High impact, low probability? An empirical analysis of risk in the economics of climate change. Clim. Change 108 (3), 519–541.

Döll, C., Döll, P., Bots, P., 2013. Semi-quantitative actor-based modelling as a tool to assess the drivers of change and physical variables in participatory integrated assessments. Environ. Model. Softw 46, 21–32.

Downing, T.E., Ringius, L., Hulme, M., Waughray, D., 1997. Adapting to climate change in africa. Mitig. Adapt. Strategies Glob. Change 2 (1), 19–44.

Dumas, P., Ha-Duong, M., 2013. Optimal growth with adaptation to climate change. Clim. Change 117, 691–710.

Estrada, F., Tol, R.S.J., Gay-García, C., 2015. The persistence of shocks in GDP and the estimation of the potential economic costs of climate change. Environ. Model. Softw

69, 155–165.
Estrada, F., Tol, R.S.J., 2015. Toward impact functions for stochastic climate change. Clim. Change Econ. 6 (04) 1550015.
Estrada, F., Botzen, W.J.W., Tol, R.S.J., 2017a. A global economic assessment of city policies to reduce climate change impacts. Nat. Clim. Chang. 7. https://doi.org/10.1038/nclimate3301.
Estrada, F., Tol, R.S.J., Botzen, W.J.W., 2017b. Global economic impacts of climate variability and change during the 20th century. PLoS One 12https://doi.org/10.1371/journal.pone.0172201. e0172201.
Fankhauser, S., Smith, J.B., Tol, R.S.J., 1999. Weathering climate change: some simple rules to guide adaptation decisions. Ecol. Econ. 30 (1), 67–78.
Fankhauser, S., Sahni, A., Savvas, A., Ward, J., 2016. Where are the gaps in climate finance? Clim. Dev. 8, 203–206. https://doi.org/10.1080/17565529.2015.1064811.
Füssel, H., 2010. Modeling impacts and adaptation in global IAMs. Wiley Interdiscip. Rev.: Clim. Change 1 (2), 288–303.
Gay, C., Estrada, F., 2010. Objective probabilities about future climate are a matter of opinion. Clim. Change 99, 27–46. https://doi.org/10.1007/s10584-009-9681-4.
Hamilton, S.H., ElSawah, S., Guillaume, J.H.A., Jakeman, A.J., Pierce, S.A., 2015. Integrated assessment and modelling: overview and synthesis of salient dimensions. Environ. Model. Softw 64, 215–229.
Hope, C., 2011. The PAGE09 Integrated Assessment Model: A Technical Description. Cambridge Judge Business School Working Paper 4.
Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. Environ. Model. Softw 21 (5), 602–614.
Kahn, M.E., 2016. The climate change adaptation literature. Rev. Environ. Econ. Policy 10, 166–178. https://doi.org/10.1093/reep/rev023.
Kelly (Letcher), R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw 47, 159–181.
Klein, R.J.T., Huq, S., Denton, F., Downing, T.E., Richels, R.G., Robinson, J.B., Toth, F.L., 2007. Inter-relationships between adaptation and mitigation. In: IPCC (Ed.), Climate Change 2007: Climate Change Impacts, Adaptation, and Vulnerability. Cambridge University Press, Cambridge chap. 18.
Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H.M., Fosu, K.Y., Gbetibouo, G., Jain, S., Mahamadou, A., Mano, R., Kabubo-Mariara, J., El-Marsafawy, S., Molua, E., Ouda, S., Ouedraogo, M., Séne, I., Maddison, D., Seo, S.N., Dinar, A., 2006. Will african agriculture survive climate change? World Bank Econ. Rev. 20, 367–388. https://doi.org/10.1093/wber/lhl004.
Lempert, R.J., Schlesinger, M.E., Bankes, S.C., Andronova, N.G., 2000. The impacts of climate variability on near-term policy choices and the value of information. Clim. Change. https://doi.org/10.1023/A:1005697118423.
Letcher, R.A., Croke, B.F.W., Jakeman, A.J., 2007. Integrated assessment modelling for water resource allocation and management: a generalised conceptual framework. Environ. Model. Softw 22 (5), 733–742.
Morice, C.P., Kennedy, J.J., Rayner, N.A., Jones, P.D., 2012. Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: the HadCRUT4 data set. J. Geophys. Res.: Atmosphere 117 (D8).
Narain, U., Margulis, S., Essam, T., 2011. Estimating costs of adaptation to climate change. Clim. Policy 11, 1001–1019. https://doi.org/10.1080/14693062.2011.582387.
National Academies of Sciences Engineering and Medicine, 2017. Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide. National Academies Press, Washington DC.
Neumann, J.E., Strzepek, K., 2014. State of the literature on the economic impacts of climate change in the United States. J. Benefit-Cost Anal. 5 (3), 411–443.
Nordhaus, W.D., 2017. Revisiting the social cost of carbon. Proc. Natl. Acad. Sci. 114 (7), 1518–1523.
Nordhaus, W.D., 2011. Integrated economic and climate modeling. SSRN Electron. J. https://doi.org/10.2139/ssrn.1970295.
Nordhaus, W.D., 2010. Economic aspects of global warming in a post-Copenhagen environment. Proc. Natl. Acad. Sci. 107 (26), 11721–11726.
Nordhaus, W.D., 2008. A Question of Balance: Weighing the Options on Global Warming Policies. Yale University Press.
Nordhaus, W.D., Boyer, J., 2000. Warming the World: Economic Models of Global Warming. MIT Press.
Oreskes, N., 1998. Evaluation (not validation) of quantitative models. Environ. Health Perspect. 106 (Suppl. 6), 1453–1460.
Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, validation, and confirmation of numerical models in the earth Sciences. Science 263, 641–646. https://doi.org/10.1126/science.263.5147.641.
Parry, M., Arnell, N., Berry, P., Dodman, D., Fankhauser, S., Hope, C., Kovats, S., Nicholls, R., Satterthwaite, D., Tiffin, R., Wheeler, T., 2009. Assessing the Costs of Adaptation to Climate Change. https://doi.org/10.1641/0006-3568(2001)051[0723:CCAFD]2.0.CO;2.
Patt, A.G., van Vuuren, D.P., Berkhout, F., Aaheim, A., Hof, A.F., Isaac, M., Mechler, R., 2010. Adaptation in integrated assessment modeling: where do we stand? Clim. Change 99 (3–4), 383–402.
Schneider, S.H., 1997. Integrated assessment modeling of global climate change: transparent rational tool for policy making or opaque screen hiding value-laden assumptions? Environ. Model. Assess. 2 (4), 229–249.
Schwanitz, V.J., 2013. Evaluating integrated assessment models of global climate change. Environ. Model. Softw 50, 120–131.
Spiegelhalter, D.J., Riesch, H., 2011. Don't know, can't know: embracing deeper uncertainties when analysing risks. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 369, 4730–4750. https://doi.org/10.1098/rsta.2011.0163.
Tol, R.S.J., 2018. Economic impacts of climate change. Rev. Environ. Econ. Policy 12 (1), 4–25.
Tol, R.S.J., Fankhauser, S., 1998. On the representation of impact in integrated assessment models of climate change. Environ. Model. Assess. 3 (1–2), 63–74. https://doi.org/10.1023/A:1019050503531. March 1.
Tol, R.S.J., Fankhauser, S., Smith, J.B., 1998. The scope for adaptation to climate change: what can we learn from the impact literature? Glob. Environ. Chang. 8 (2), 109–123.
van den Bergh, J.C.J.M., Botzen, W.J.W., 2014. A lower bound to the social cost of CO2 emissions. Nat. Clim. Chang. 4, 253–258. https://doi.org/10.1038/nclimate2135.
Vedrenne, M., Borge, R., Lumbreras, J., Rodríguez, M.E., 2014. Advancements in the design and validation of an air pollution integrated assessment model for Spain. Environ. Model. Softw 57, 177–191.
Walker, W.E., Lempert, R.J., Kwakkel, J.H., 2013. Deep uncertainty. In: Encyclopedia of Operations Research and Management Science. Springer US, Boston, MA, pp. 395–402. https://doi.org/10.1007/978-1-4419-1153-7_1140.
Warren, R., Hope, C., Mastrandrea, M., Tol, R.S.J., Adger, N., Lorenzoni, I., 2006. Spotlighting the impacts functions in integrated assessments. Research report prepared for the stern review on the economics of climate change. Available at: www.tyndall.ac.uk.
Weitzman, M.L., 2012. GHG targets as insurance against catastrophic climate damages. J. Public Econ. Theory 14 (2), 221–244.
Weitzman, M.L., 2009. On modeling and interpreting the economics of catastrophic climate change. Rev. Econ. Stat. 91, 1–19. https://doi.org/10.1162/rest.91.1.1.
Yohe, G., Tol, R.S.J., 2002. Indicators for social and economic coping capacity—moving toward a working definition of adaptive capacity. Glob. Environ. Chang. 12 (1), 25–40.